Modeling Statistics of Fish Patchiness and Predicting Associated Influence on Statistics of Acoustic Echoes

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LONG-TERM GOALS

To accurately describe the statistics of acoustic echoes due to the presence of fish, especially in the case of a long-range active sonar. Toward this goal, fundamental advances in the understanding of fish behavior, especially in aggregations, will be made under conditions relevant to the echo statistics problem.

OBJECTIVES

To develop new models of behavior of fish aggregations, including the fission/fusion process, and to describe the echo statistics associated with the random fish behavior using existing formulations of echo statistics.

APPROACH

The research begins with development of new advanced models of fish behavior inspired by, and grounded by, existing 3-D images of fish aggregations. These images are derived by multi-beam acoustic systems. Key parameters to be observed and modeled are the fission/fusion rate of the

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aggregations. Concurrent with the modeling of fish behavior, statistics of fish aggregations, as they become available, will be incorporated into an existing general formulation for echo statistics. The results of this echo statistics model will, in turn, help to drive further development of the fish behavior model. In parallel to these efforts, other groups in the BRC will be conducting measurements. The Stanton/Weber/Grunbaum group participated in planning those experiments which may have a component that reveals key aspects of fish behavior and, in turn, contribute to the modeling.

Stanton oversees the entire project as well as works with Weber on incorporating fish behavior models into echo statistics predictions. Weber also analyzes images of fish aggregations that he and others have collected. Grunbaum develops the fish behavior models. The work also involves informal collaborations with Chris Wilson of NOAA Alaska Fisheries and Ben Jones of NPS.

WORK COMPLETED

Major milestones were reached this year and two papers were submitted (one of which was published) to refereed journals. Both papers involved modeling fish behavior, one comparing past models of behavior with 3-D multi-beam acoustic data and the other involving development of a new model. In addition, statistics of newly collected 3-D multi-beam data were determined in preparation for comparison with the new model. Finally, preliminary work was completed in computing echo statistics for various assemblages of fish as detected by a long-range mid-frequency sonar in an ocean waveguide.

1. Comparing previous competing behavior models with 3-D multi-beam data
While the new model was being developed, previous competing models were compared with published 3-D multi-beam data. This helped to develop methods for comparing the statistics of static behavior properties as observed in these acoustic systems as well as provide information inferred on the dynamic behavior of the fish. The Niwa and Anderson models were compared with 3-D multi-beam data collected by Paramo and Gerlotto. The data were consistent with the Anderson model in that both the data and model had a mode in the statistics of fish school dimensions (whereas the Niwa model does not have a mode). This suggests that the assumptions in the Anderson model on fish dynamics apply to these fish—the rate at which fish exit the school is proportional to school size (Bhatia et al., submitted).

2. New model for fish school behavior
A novel approach that was started last year has reached a milestone this year towards understanding fission, fusion, and migration of social groups by assuming a high level of sensory and cognitive function by interacting individuals (Grunbaum, 2012). Simulations based on this model show all of these behavioral aspects, as illustrated in the time series of fish distribution in Figure 1.

Nearly all current models of social interaction are "zone models" which assume that characteristics of animal groups such as schools, swarms and flocks arise from individuals' immediate responses to the relative positions and velocities of a small number of nearest neighbors. While there is little question that position- and velocity-dependent responses are crucial to social grouping, current zone models commonly predict that large groups (that is, groups in which individuals in different parts of a group must interact indirectly through many individuals between them) should be fragile and therefore rare or transient. However, natural groups are frequently large and stable. In other settings, natural populations that are sparse or distributed in numerous small groups nonetheless maintain common orientation across groups. In most current zone models, directionality can be maintained only by frequent

encounters between individuals and groups, and so is unlikely in sparse populations at reasonable levels of behavioral and physical random forcing.

The new model assumes an additional cognitive layer in fish schooling behavior, in which encounters with neighbors are used as input data on which to base statistical estimates of the density and movement characteristics of the local population. The key idea is that each individual is continuously updating its understanding of the intent of its neighbors, and basing its own decision-making on this understanding. Thus, social individuals can glean information even when the instantaneous position and velocity of neighbors are quite different from overall movement patterns, or when neighbors are so sparse that encounters with them are rare.

The above line of reasoning suggests a new hybrid model that combines agent-based "Lagrangian" movement rules with a "Eulerian" distribution of population density and flux, together with local distributions of orientation angle. This hybrid approach has multiple advantages from the perspective of understanding acoustic signatures of fish in real-world settings. One is computational tractability: Agent-based models of social grouping are inherently N^2 computations, where N is the number of individuals. (Specifying maximum interaction distances can enable subdivision of the habitat into non-interacting parts, but computational requirements remain large for dense groups.) The hybrid model executes parallel simulations, in which the estimates of local population characteristics evolve as partial differential equations, and the individuals respond to estimates as autonomous agents. Hence, there is no N^2 calculation required. Another advantage of our hybrid approach is that the statistical distributions calculated during social simulations (population density, orientation angles, etc.) are directly relevant to estimates of acoustic signatures.

The hybrid modeling assumes a Bayesian framework for local estimation of population movement. For example, for estimates of local density, we assume each individual maintains a Bayesian updating scheme for determining the expected value and uncertainty associated with the Poisson distribution of neighbors. In a standard updating scheme, appropriate for statistically stationary neighbor distributions, the uncertainty decreases monotonically with ongoing sampling. In application to schooling, in which populations move and therefore are not statistically stationary, we discount the predictive value of old information. Hence, an individual's uncertainty about local density and direction fluctuates downwards when informative samples occur frequently and upwards when such samples are rare.

Current work focuses on extracting parameters for the new modeling framework from individual-level behavioral laboratory and field observations, and from population-level acoustic transects for natural populations. The main challenge in model-fitting is the number of initially unconstrained parameters to be optimized. Our immediate approach is to take advantage of the unique dataset generated for the Eastern Bering Sea, in which transects were repeated many times at relatively short intervals (see Section 3). These data enable us to adopt a "divide-and-conquer" strategy: The model assumes that fish use spatial memory in schooling, and that a time scale characterizes the duration over which historical events continue to influence schooling decisions. For any given choice of that time scale, we can compute fishes' cognitive assessments of school distributions in their neighborhoods, using repeat transect data. For example, if the interval between transects is 15 minutes, and the memory timescale is 30 minutes, then fish at transect i will be basing schooling decisions based on fish distributions in transects i-2, i-1 and i. A model simulation that is initialized with the observed fish distribution in transect i is then a prediction for the fish distribution at transect i+1. By systematically varying the time scale and behavior parameters, we can determine parameter choices that optimize correspondence between observed and modeled fish distributions. We will then use optimal or near-optimal parameters

to assess dynamics likely to have led to observed fish distributions in the entire Eastern Bering Sea data sets.

3. High resolution images of fish aggregations derived from acoustic multibeam data

Multi-beam data analysis has focused on data collected in the Eastern Bering Sea (EBS) during both 2010 and 2012. These data were collected using a Simrad ME70 multibeam echosounder as part of the NOAA Alaska Fisheries Science Center (NOAA-AFSC) acoustic/trawl walleye pollock surveys. Data collections from both years represent multiple (approximately 9) week survey efforts aimed at broad-scale stock assessments in the EBS, and ME70 data have been made available to this project courtesy of Chris Wilson (NOAA-AFSC). Most of the data were collected along widely spaced (~40 km) transects, and for the purposes of this research are considered to represent a 'snapshot' of the pollock aggregations present in the EBS. During the 2012 data collection effort, NOAA-AFSC also conducted repeat transects at our request and with our guidance on two occasions. This resulted in ~1 nmi long transects that were repeated every 10-15 minutes, with 24 transects on the first occasion and 14 transects on the second occasion. Data analysis has thus far been focused on population level statistics, where comparisons to behavioral models may help define or bound aggregation behaviors (e.g., fusion and fission rates).

ME70 data representing 8 days of survey effort in July 2010 were analyzed to form clusters of volumetric backscatter representing mid-water pollock aggregations (Figure 2). These data cover a region extending from 176ºW to 179.5ºW and 58ºN to 62.5ºN. Mid-water trawls (N = 43) conducted in this region caught 98% pollock by weight. The ME70 data were processed to

    a. remove potential seabed returns and sidelobe contamination

    b. remove data below a threshold of Sv = -60 dB (independent of beam angle)

    c. remove spatially isolated targets that are considered 'speckle' noise

    d. cluster, and uniquely label, data that are within 25 m of each other horizontally and 5 m of each other vertically

    e. extract metrics describing each cluster including the cluster volume, V, maximum vertical extent, H, and maximum horizontal extent, L.

49,650 clusters of fish were extracted for the 8 day period. Histograms of their effective size, $V^{1/3}$, vertical extent, and horizontal extent are shown in Figure 3. Also shown are best fits of the data to the models of Anderson [1981] and Niwa [2003], in similar fashion to Bhatia et al [submitted]. Neglecting issues that may arise from the ME70 finite field of view and range/angle-dependent resolution, the data suggest that the pollock aggregations have a high aspect ratio: the mode of the horizontal extent is approximately 6 times greater than the mode for the maximum vertical extent. The data can be fitted quite closely to the Anderson model, which assumed disk-like aggregations of fish and modeled the diameter of schools.

An important caveat in the population statistics shown in Figure 3 is that the data represent aggregations of both juveniles and adults, nighttime and daytime behaviors, other environmental covariates, and possible 'contamination' from other species. To examine this issue further, we have extracted population statistics from the 2012 repeat transects. The first set of repeat transects targeted small, dense fish aggregations ("cherry balls") that were fully contained within the ME70 field of

view. The second set of repeat transects targeted dense aggregations that could be acoustically mapped, but which likely extended outside of the field of view. For the first set of repeat transects (Figure 4), the fish aggregations observed on consecutive passes appeared to be uncorrelated, and were largely constrained to dense aggregations at water depths less than 80 m with a large, widely-spaced aggregation of targets below 80 m. The second set of repeat transects exhibited dense aggregations of fish throughout the water column, with a quasi-continuous distribution of fish below 80 m water depth and relatively well-separated aggregations in the upper portion of the water coumn (Figure 5). These data were processed similarly to the 2010 ME70 data, except that rather than cluster the data based on an *a priori* assumption about horizontal and vertical 'linking' distances, the data were contoured based on volume scattering strength. Aggregation metrics were subsequently calculated at the contour level representing a fish density 100x less than the peak density. This approach made it possible to treat discrete and quasi-continuous aggregations using the same methodology. The distribution of the effective school horizontal radius is shown in Figure 6 for the 1st set of repeat passes ('subset 1'), and for the second set of repeat passes for fish observed in the upper 80 m of water ('subset 2, upper 80 m'), below 80 m ('subset 2, below 80 m'), and for a 10 m thick layer between 90-100 m ('subset 2, 90-100 m'). Each distribution appears quite similar and, like the larger population of aggregations analyzed from the 2010 data, fit a power-law distribution of approximately L^{-3} for the larger aggregation sizes.

Several questions related to these data are currently under investigation, including the potential influence of measurement area and the possible reasons behind the similarity of the aggregation size distributions under seemingly different circumstances.

4. Echo statistics due to various aggregations of fish detected by a mid-frequency long-range sonar
As part of the goal of characterizing echo statistics due to aggregations of fish detected by a long-range sonar, calculations were made involving several simple cases (Fig. 7). Reverberation was predicted for a mid-frequency sonar deployed near the surface in an ocean waveguide (many km long). Two sets of calculations were made, one with the community standard PE code, and the other with a numerically efficient code that we developed. Several example calculations were made with 1, 2, 5, and 10 identical small aggregations of fish in the waveguide. The calculations demonstrate the degree to which the statistics are non-Rayleigh, with the "tail" of the echo probability density function (PDF) increasing with decreasing numbers of aggregations.

RESULTS

We have reached milestones of new understanding along several directions: 1. Modeling of fish behavior. The advanced modeling of fish behavior has yielded promising results. Fission, fusion, and migratory behavior of the fish are being modeled. These results use a hybrid approach that integrates both intelligence of the fish in nearest neighbor interactions as well as group behavior. Initial modeling of 3-D data has given information on the rate at which fish exit a school. 2. 3-D multibeam data. Examination of data from several locations in the world has consistently exhibited a mode in the statistics of school dimensions, which provides information for the modeling in #1 above. 3. Echo statistics from a long-range sonar. The degree to which the tail of the echo PDF is non-Rayleigh depends directly upon the number of patches of fish are in the sonar beam and increases with decreasing numbers of aggregations.

IMPACT/APPLICATIONS

The modeling of fish behavior represents an advancement of the fundamental understanding of fish behavior, with new capability (fish intelligence) and the grounding with observed images of fish aggregations in the ocean. The initial modeling of echo statistics from a mid-frequency sonar with several simplistic examples of fish aggregations demonstrates the clutter characteristics relevant to Navy ASW applications. Once the behavior model is connected with the echo predictions, we will have a significant tool for predicting sonar performance associated with the presence of fish.

PUBLICATIONS

Grunbaum, D. (2012) A spatially explicit Bayesian framework for cognitive schooling behaviors. Interface Fous. doi: 10.1098/rsfs.2012.0027 [published, refereed]

Bhatia, S., T.K. Stanton, J. Paramo, and F. Gerlotto (submitted), "Modeling statistics of fish school dimensions using 3-D data from a multibeam sonar," submitted to J. Theor. Bio. [submitted, refereed]
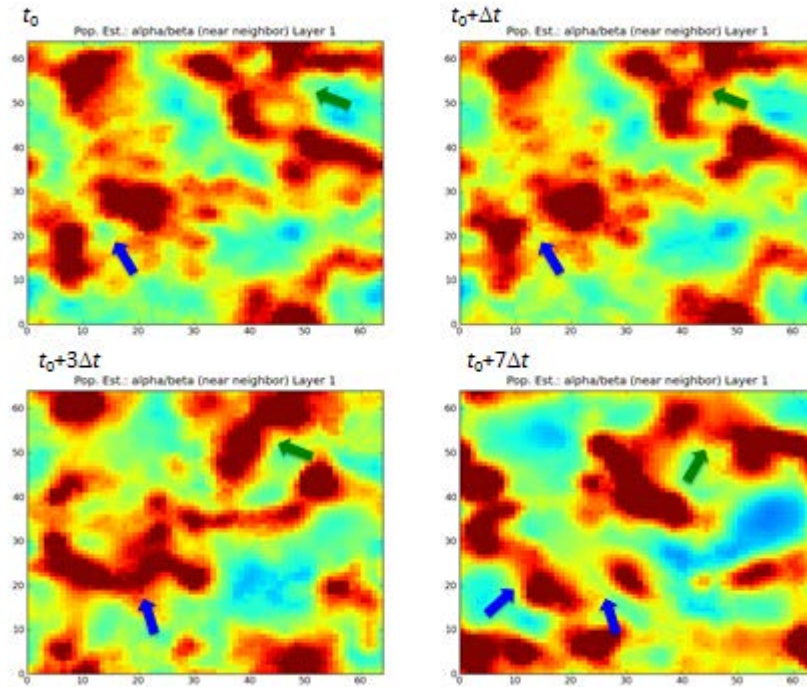
Figure 1. Fission-fusion dynamics in the cognitive schooling model, reflected in population-level density distributions at four sequential time steps (note varying time increments between images). Blue arrows indicate approach and then fusion of two groups, followed by a subsequent fission event and incipient fusion with another group. Green arrows indicate a simultaneous approach/fusion/fission sequence in a different part of the simulation domain.
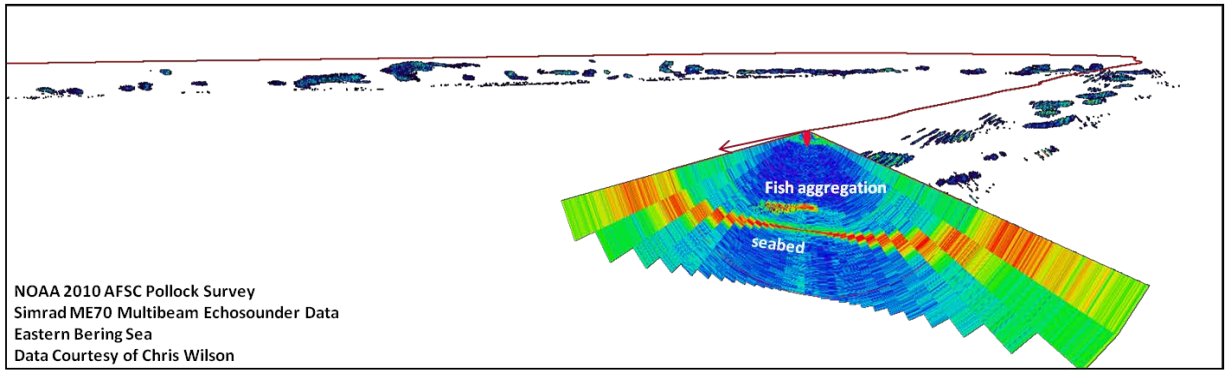
Figure 2. Example of Simrad ME70 multibeam data collected by NOAA-AFSC in the Eastern Bering Sea. A single ping of data representing a 'slice' of the water column is shown in the foreground. Target detections representing aggregations of walley pollock are shown in the background. The ship's track line is shown in red.
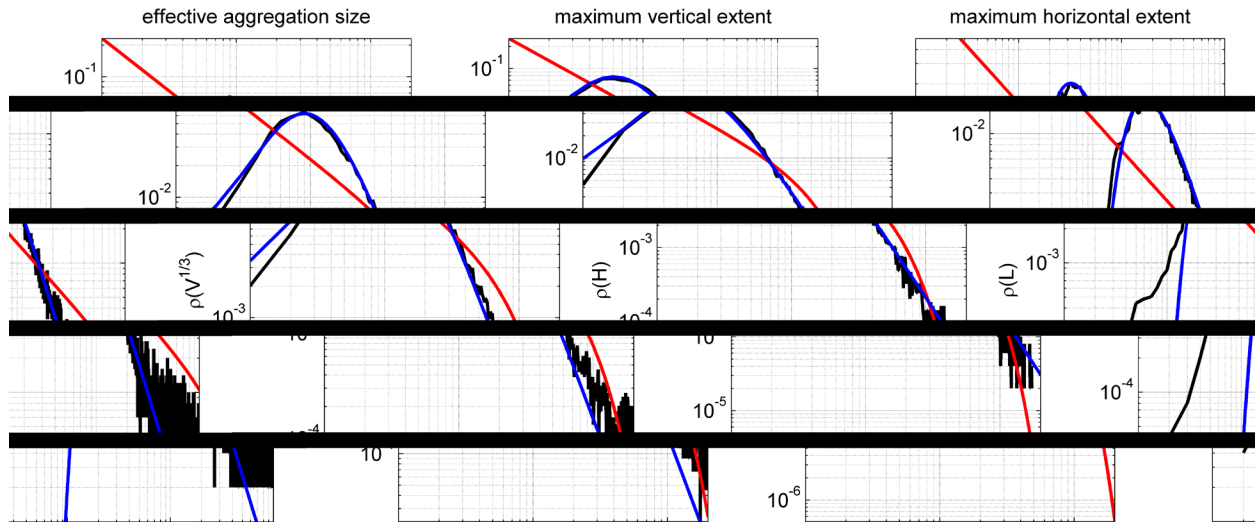

Figure 3. Statistics of fish school dimensions. Black line: Size distributions for effective size, maximum vertical extent, and maximum horizontal extent, as measured by NOAA-AFSC in the Eastern Bering Sea (See Fig. 1). Red line: Niwa's model. Blue line: Anderson's model. Note that the axes change for each plot.
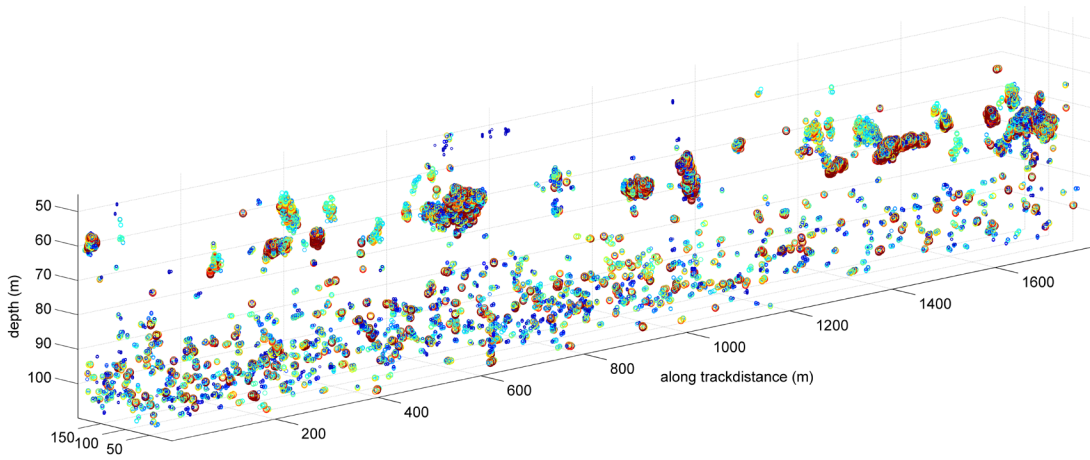
Figure 4. An example transect from the first set of repeat transects (school subset 1) in the Eastern Bering Sea, with dense aggregations of fish in the upper 80 m and a loose aggregation of fish below 80 m.
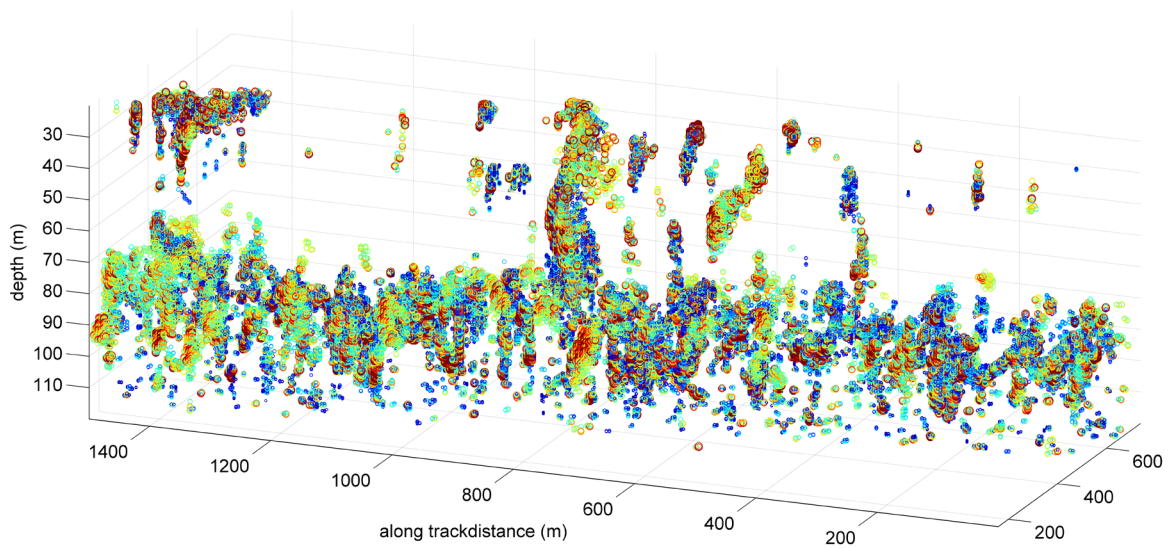

Figure 5. An example transect from the second set of repeat transects (school subset 2) in the Eastern Bering Sea, with dense aggregations of fish found throughout the water column.
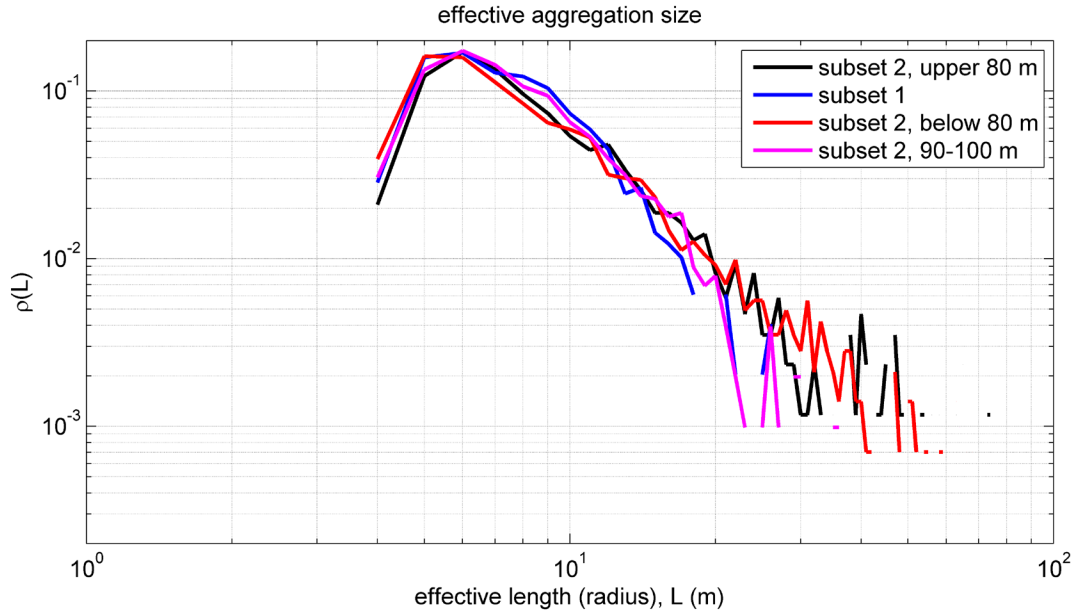
Figure 6. Distributions of effective sizes of fish aggregations (based on Fourier descriptors) were calculated for both subsets of fish data (see legend) from Eastern Bering Sea, and appear similar in all cases. For values beyond the mode, there is a power-law appearance (similar to Figure 3) in all cases, with the possible exception of subset 1.
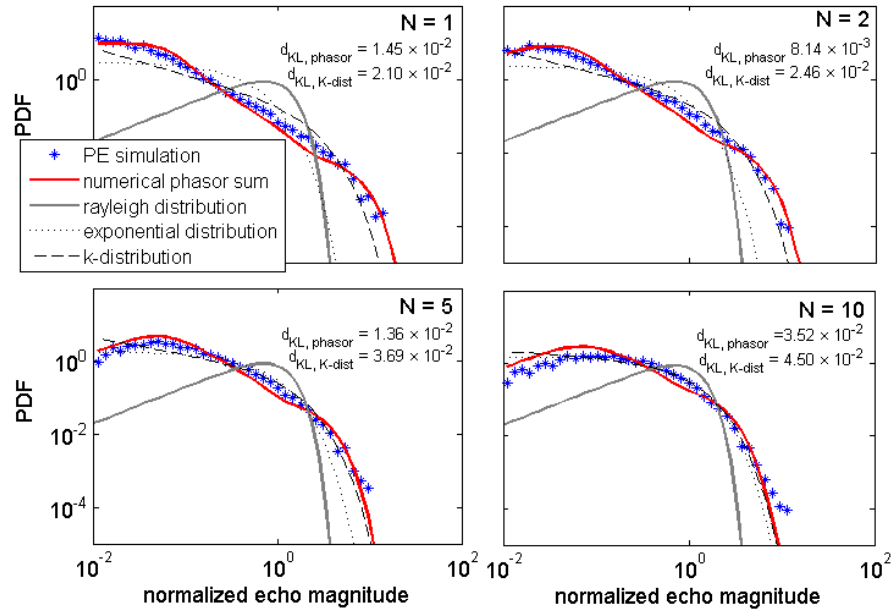

Figure 7. Modeled echo statistics from a mid-frequency sonar in a waveguide with small patches of fish present. Four examples are given in which there are 1, 2, 5, and 10 identical patches present. From Jones (2012).